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Model Uncertainty in Ecological Criminology: An Application of Bayesian Model Averaging With Rural Crime Data

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Abstract

In this study we explore the use of Bayesian model averaging (BMA) to address model uncertainty in identifying the determinants of Midwestern rural crime rates using county level data averaged over 2006-07-08. The empirical criminology literature suffers from serious model uncertainty: theory states that everything matters and there are multiple ways to measure key variables.By using the BMA approach we identify variables that appear to most consistently influence rural crime patterns. We find that there are several variables that rise to the top in explaining different types of crime as well as numerous variables that influence only certain types of crime.

Introduction

The empirical ecological criminology literature is vast and richly interdisciplinary. But there are at least three problem areas that have created significant confusion over the policy implications of this literature. First, the theoretical literature basically concludes that "everything matters" which makes empirical investigations difficult specifically related to model uncertainty. Second, there is sufficient fragility within the empirical results to cast a pall over the literature (Chiricos, 1987; Patterson, 1991; Fowles and Merva, 1996; Barnett and Mencken, 2002; Bausman and Goe, 2004; Chrisholm and Choe, 2004; Messner, Baumer and Rosenfeld, 2004; Phillips, 2006; Authors). Donohue and Wolfers (2005) along with Cohen-Cole, Durlauf, Fagan and Nagin (2009) note, for example, that the extensive empirical literature seeking to test the deterrent effect of capital punishment has yield nothing but contradictory and inconclusive results.

Third, the limited empirical literature that focuses on rural crime suggests that what might help explain urban crime does not apply to rural (Authors). Lee, Maume and Ousey's (2003) work, for example, on comparing the role of poverty concentration, a socioeconomic characteristic that is a central driver of crime in nearly all theories of crime, on rural and urban crime. They find that for urban higher poverty concentrations are associated with higher violent crime rates, as predicted by theory, but rural poverty concentration plays no role in

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helping explain rural violent crime. A comprehensive theory of crime should not have disclaimers such as "it works for cities but not small towns."

Model uncertainty exists when the research is (a) uncertain about the structure of the model, (b) uncertain about the estimates of the model parameters, even if we know the structure of the model, and (c) unexplained random variation in observed variables even when we know the structure of the model and the values of the model parameters (Chatfield 1995).This can range from model specification (e.g., omitted variable bias) to variable definition to functional form (e.g., linear vs. non-linear) to incorrect assumption about the error structure of the statistical processes. Or as Western (1996, p167) states it: "(1) the selection of variables, (2) the choice of functional form, and (3) the stochastic specification."

In the empirical ecological criminology literature model uncertain comes in many forms including theories that tell us "everything matters" or a "laundry list" of potential control variables (Western 1996, 2001). Multiple ways to specific variables can also contribute to the problem of model uncertainty. For example, Chisholm and Choe (2004) note that in the criminology literature income measures have ranged from median and average family and/or household income, to per capita income, to wages per job and what appears to be modest changes in variable definition can lead to inconsistent results. Here model uncertainty centers not only on the selection of the right set of regressors but also how specific regressors are to be measured.

Model uncertainty is also a concern when we consider different types of crime. This source of uncertainty has often been referred as aggregation bias in the criminology literature. For example, the drivers of domestic violence are fundamentally different from college students engaging in a bar fight or the decision of a burglar to use a weapon. Our theories of crime generally talk in terms of criminal activity in the aggregate and when we think about or attempt to model different types of crime model uncertainty again becomes a concern.

There exist several "model selection methods", one specific type of model uncertainty, which have been suggested as a means to select a final set of regressors. These methods range from step-wise regression where variables are systematically introduced into the model and some criteria such as changes in the equation F statistic, $\bar{R}^2$ or Mallows' C_p statistic are tracked to determine if a variable should or should not be included in the final model. Other criteria include the Amemiya criteria (PC),Akaike Information Criteria (AIC), Sawa Bayesian Information Criterion and/or the Schwarz Bayesian Information Criterion (BIC) as well as the Jeffreys-Bayes posterior odds ratio, among others (see Burnham and Anderson 2004, Judge et al., 1985, Kuha 2004 and Posada and Buckley 2004 for formal discussions). Here models with different variable specifications yield some type of selection criteria metric (e.g., F, $\bar{R}^2$, C_p, AIC, BIC, etc.) and the model with the highest (or lowest depending on the criteria metric) is selected as the"correct" model.Holleran, Beichner and Spohn (2010), for example, recently used the Bayesian Information Criterion (BIC) as the primary model selection criteria in a study of arrest and prosecutions patterns in rape cases using data for Kansas City, Missouri and Neema and Böhning (2010) use the BIC and AIC in modeling burglary and murder in Namibia.

As noted by Fowles and Merva (1996 p168) within the empirical criminology literature:

> Conventional reporting often presents *t* statistics or *p* values for the best-fitting results or for those that may conform to a researcher's prior beliefs. Usually the best fit is uncovered after a model search. In a model search, variables are typically dropped or introduced until search criteria are satisfied.

But these approaches are not without their limitations ranging from assertions of "data mining" to the selection of arbitrary threshold criteria to problems associated with sample and parameter space sizes and in a decision theory context vagueness as to the corresponding loss or risk function. In essence, there is no theoretical justification for using one method or criteria over another and if different selection methods yield different results the analyst is left at square one.As noted by Raftery (1995) it is possible that several of these alternative models can fit the data almost equally as well yet different selection methods can yield vastly different models.

Perhaps a more fundamental problem with this approach is the implicit assumption that the final model specification is the only one consider out of many possibilities.By discarding all models except for one can yield misleading results because by selecting one model from a large number of models one increases the probability of finding significant variables by chance alone (Raftery 1995). Indeed, Fowles and Merva (1996 p168) conclude that "[t]he selective reporting of conventional statistics based on this sort of search may be misleading since the sampling properties of the estimators are not known."

As noted by Hansen (2007) model averaging has developed as an alternative to model selection methods. In model averaging inferences are based on a weighted average over all models rather than one model. Draper (1995) and Wintle, et al. (2003) observe that there are two approaches to model averaging: discrete and continuous. The ultimate goal of discrete model averaging is to arrive at a set of plausible models that can be weighted by some criteria such as Mallow's C_p in the case of Hansen's (2007) least squares model averaging. The weightings reflect the trustworthiness of each model; models that are more consistent with the data receive higher weights in the final averaging.

Discrete model averaging is discrete because the final averages are constructed from a predetermined subset of all possible models. Here the analyst selects a subset of potential models over which to conduct the averaging. Continuous model averaging centers on the idea of model expansion where a single structural choice model is expanded in directions suggested by an analytic search. Markov Chain Monte Carlo (MCMC) processes provide one mechanism by which iterative sampling of the full range of prior distributions of the parameters is undertaken. By using a weighted average of a wide range of possible model specifications inferences can be made as to what the final set of regressors should contain and what the parameter estimates look like.

Bayesian model averaging (BMA) has become a widely used approach to continuous model averaging.The challenge with the BMA approach is that it provides at least three different ways to move forward with the results: examinethe full specification using the posterior mean (weighted average of the posterior means in the separate models) coefficient for each variable included in our set of variables (i.e., continuous model averaging); focus on the frequency of variables that are included in models that have a posterior probability greater than some selected threshold (i.e., discrete model averaging); finally focus on the single model with the highest posterior probability to determine which variables are to be further analyzed (i.e., discrete model averaging). We suggest that by looking at the BMA results from these three different angles we gain better insight into the drivers of crime.

The intent of the study reported here is to explore the application of Bayesian model averaging to address model uncertainty in our understanding of rural crime in the U.S. Today, BMA has been widely used across a range of disciplines as a variable reduction method when too many potential regressors lead to model uncertainty. The approach has been applied to improve the methods of weather forecasting (Raftery, et al., 2005) and modeling ecological systems (Wintle, et al., 2005) to economic growth (authors; Magnus, Powell and Prüfer, 2010) and demography (Murphy and Wang 2001). The BMA approach is finding wide application in medical research where model uncertainty is prevalent (e.g., Yeung, Bumgarner and Raftery 2005). Although Bruce Western (1996, 2001) has considered the notions of model uncertainty in macrosociology and has explicitly suggested the use of Bayesian model averaging, to the best of our knowledge the BMA approach has seen only limited application in the criminology literature (e.g., Cohen-Cole, et al. 2009; Rafterty 1995).[1]

To explore the potential use of BMA as a means to gain insights into the determinants of rural crime we use a sample of non-metropolitan counties from the Midwestern states. By focusing attention on rural we hope to address a weakness to the literature identified by Lee and Ousey (2001) and Donnermeyer, Jobes and Barclay (2006); specifically rural crime has largely been ignored by criminologists. Although Lee and Thomas (2010) note that there has been growing interest in rural crime the breath of the available empirical rural criminology literature is still too narrow to draw any reasonable conclusions.We introduce 43 potential determinants of crime, classified into seven different categories including components of both violent and property crime. The FBI

[1] In a discussion of a BMA procedure written for the programming software *R*Raftery, Painter and Volinsky (2005) use crime data as an example and Raftery (1995) uses crime data as an example in a discussion of alternative model selection criteria. In both case the discussion of crime is secondary to the development of Bayesian methods.

Unified Crime Reports data are averaged over the 2006-07-08 period and all other data are from 2007 unless otherwise noted.

Because we are considering only the specification of the rural crime models we are not considering all potential sources of model uncertainty. We do not consider function form and assume a simple linear form. Nor do we consider the error structure of the underlying data generating processes. Specifically we assume that the error structure is well-behaved. We do address to a limited extent the sensitivity of the results to variable definitions by looking at different measures of income and poverty.

Beyond these brief introductory comments the manuscript is composed of five additional sections. First, we provide a brief overview of the theoretical criminology literature followed by an outline of the Bayesian model averaging method. Our selection of variables is then discussed in relation to the theoretical criminology framework. Empirical results are then presented and discussed and the study closes with a discussion of future work.

Overview of Criminology Theory

From our perspective there are three core or umbrella theoretical approaches that dominate the ecological empirical criminology literature: the Chicago School of social disorganization which takes a macro, ecological or community perspective and two micro or individual focused theories, anomie or strain, and rational choice. Although each approach tackles crime from a different direction there are significant and important overlaps. Where these theories overlap model uncertainty is reduced but where they do not overlap leads to greater model uncertainty.

Social disorganization or social cohesion theory, widely known as the Chicago School of Criminology due to the pioneering work of Park and Burgess (1925) and Shaw and McCay (1931, 1942, 1969), emphasizes social, economic and political forces at the ecological level. Attention is focused on social capital broadly defined and notions of density of acquaintance across the community, village or neighborhood and is concerned with the socioeconomic deterioration of places and the social ties that link neighbors (Thorbecke and Charumilind 2002; Lederman, Loayza and Menendez 2002; Bouffard and Muftic 2006).[2]Spano and Nagy (2005) suggest that social disorganization theory can be restated simply as structural factors influence social networks which in turn influences social control. Social control in turn drives crime.

As noted by Jobes and his colleagues (2004), Wells and Weisheit (2004), Berg and DeLisi (2005),Donnermeyer (2007) and Li (2009) social disorganization theory has dominated the sociology literature that has examined rural crime. Indeed, Bellair and Browning (2010: p497) conclude that "[s]ocial disorganization theory is one of the oldest and among the most well-respected sociological approaches to community crime." Still, many such as Reisig and Cancino (2004) argue that social capital is too broad of a concept with respect to crime and should be more narrowly focused.

Sampson (2002, 2006) has argued that the notion of the village, neighborhood or community underpinning social disorganization theory is outmoded and to fully understand crime one must look at the

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2 Following the work of Coleman (1988), Flora and Flora (1993), Putnam (1993, 1995, 2000), and Turner (1999), Shaffer, Deller, and Marcouiller (2004) offer the following definition of social capital:

> Social capital refers to features of social organization such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefit. Networks of civic engagement foster norms of general reciprocity and encourage the emergence of social trust. Social capital consists of the social networks in a community, the level of trust between community members, and local norms. These networks, norms and trusts help local people work together for their mutual benefit. (pp. 203–204)

Such a broad definition of social capital is attractive from a conceptual perspective, but it creates serious problems for research interested in developing specific empirical metrics.

behavior at the micro or individual level and how the individual is influenced by the community. Lee and Thomas (2010) and their study of U.S. rural crime follow the lead of Tolbert and his colleagues (1998, 2002, 2005) and talk in terms of "civic community". Here the idea of social networks (i.e., the community, village or neighborhood), a key element to social disorganization theory, is not sufficient to understand crime. Rather one must think in terms of the willingness of the individual to become engaged in the community in a civic manner. The idea is that there is a fundamental difference between being "networked into the community" and willingness to engage.

Mazerolle, Wickes and McBroom (2010) build on the work of Sampson (2002, 2006) and talk of "collective efficacy" and the willingness of individuals to become engaged. Social networks are insufficient to deter crime and there must be a willingness to become engaged which acts as a deterrent to criminal activities. Belliar and Browning (2010) use the terminology of "informal control" and again how the concept of social networks is not sufficient. By moving beyond the broad-based idea of social disorganization theory and the role of social networks (or community, village or neighborhood) to think in terms of "civic community," "collective efficacy" and "informal control" helps focus on the willingness of the individual to become directly involved in helping deter crime. This can range from the willingness to participate in neighborhood watch programs and calling the police, but also willingness to work with the police to help solve and prosecute crime.

In rural density of acquaintance can be high and everyone knows everyone else but residents may be unwilling to engage law enforcement if a crime is committed. Rural residents are more likely to keep community problems to themselves by viewing crime as a personal matter and not seek the help of law enforcement agencies (Laub 1981). As noted by Weisheit and Donnermeyer (2000), rural law enforcement personal often voice frustration because of the conservative nature of many rural residents. Many people in rural areas simply prefer to handle their own problems without seeking help from "outside". In a sense, social networks, density of acquaintance or social capital can be high but engagement with respect to crime may be low.

From a modeling uncertainty perspective social disorganization theory the notion of social capital is too vague to lend itself to rigorous empirical testing. The short-comings of earlier empirical studies to link broad notions of social capital to crime have driven much of the rethinking of social disorganization theory outline above. Attempts to refine the thinking around social disorganization theory and notions of social capital are, in our framework, attempts to address model uncertainty from a theoretical perspective.

Anomie or strain theory focuses on conflicts between goals and means to achieve those goals (Fay 1993). Unlike social disorganization theory that looks at ecological or community (i.e., village or neighborhood) level, anomie theory tends to focus on individuals and behavior of those individuals adapt within the community setting. The movement to "don't snitch" in certain inner-cities conveys how personal attitudes toward crime can be influenced by the larger community. While "civic community," "collective efficacy" and "informal control" helps focus on the willingness of the individual to become directly involved in helping deter crime anomie theory focuses on the thinking of the potential criminal. In what Baumer and Gustafson (2007) refer to as Merton's (1938, 1968) classic anomie theory there exists conflicts between the economic desires of the individual and the ability to achieve those desires. Unequal distribution of economic resources, wealth and/or income creates an "envy affect" (Kelly 2000) where those at the lower socioeconomic spectrum are jealous of those that have higher socioeconomic status. There is a level of frustration where the poor either do not have the skills or the means to achieve higher levels of income and/or wealth. Unsuccessful individuals become alienated from the community, social norms from the individual's perspective come into question, and the strain results in criminal activity.

An additional element of anomie theory is the explicit allowance of acceptable alternative means to achieving an end, referred to as innovation by Merton (1968). A traditional example used within the literature is the powerful draw of illegal drug activity in the presence of few economic opportunities. While drugs are generally associated with urban crime, the rise of methamphetamine in many rural communities is creating a rural parallel (Weisheit 2008). For low income persons, generally youth and young adults, faced with the choice of achieving limited economic success through low paying service jobs the potentially highly profitable illegal drug trade become very attractive. Classical anomie theory suggests that within stressed economic situations (e.g., unemployment, low employment opportunities, poverty, high levels of income inequality) any means possible to achieve one's goals becomes acceptable behavior.

Baumer and Gustafson (2007) assert that there has been a resurgence of interest in anomie theory as it relates to crime due to the introduction of "institutional" or "contemporary" anomie theory as developed by Messner and Rosenfeld (1994/2001/2007, 1997, 2006). While Merton focused on economic conditions (i.e., economic conflict, economic inequality, economic envy effects) contemporary anomie theory introduces the role of non-economic institutions such as education, political and family. Social structure, as thought about through these institutions, matters. In the end, crime is a product of the balancing of these different institutional elements. If economic outcomes dominate and a philosophy of "the ends justify the means" is acceptable then crime is acceptable and it will occur. As in social disorganization theory community engagement through a range of different institutions moves our thinking about why crime occurs in one community but not another forward.

Rational choice theory, which has been within the sociology literature for many years and can be traced back to Beccaris' writings in 1764, was introduced into the economic literature by Fleisher (1963, 1966a, 1966b), and Ehrlich (1973, 1975), but it is broadly attributed to the Nobel winning economist Gary Becker (1968, 1993). This view of thinking about crime hypothesizes that crime is the product of rational decision making by individuals who are attempting to maximize economic well-being by comparing the benefits of crime versus the costs of apprehension and fines and/or imprisonment. If the potential "loot" was sufficiently large, then the choice to commit a crime is rational. Economists maintain that the power of the rational choice theory is that it is rooted on deductive theory of individual behavior that allows for direct and more exact empirical testing. Specifically, the level of model uncertainty is minimized. Formal derivations of the rational choice theory are available in Chiu and Madden (1998) and Chisholm and Choe (2004).

On face value classical anomie as advanced by Merton and rational choice theory appear to be two sides to the same theory. What separates the two is the notion of conflict and envy effects. In classical anomie theory and more explicitly institutional anomie theory socially acceptable behavior plays an important role; economic frustration overrides what the individual may view as socially unacceptable behavior. Despite the moral threshold of the potential criminal being included in the cost-benefit calculations of the potential criminal, in traditional rational choice theory norms and acceptable behavior are delegated to the backburner.

More recent derivations of the rational choice theory, however, have formally introduced the concept of social capital in the spirit of anomie and social disorganization theory (Fajnzylber, Lederman and Loayza 2002; Lederman, Loayza and Menéndez 2002; Messner, Baunmer and Rosenfeld 2004; Matsueda, Kreager and Huizinga 2006; Authors). Here social capital directly enters into the likelihood of being captured; ignoring the complexities of institutional anomie theory communities with higher levels of social capital are more likely to have neighbor watch-type programs or are willing to work with law enforcement agencies when investigating a crime. Potential criminals will explicitly consider levels of social capital and avoid communities with high levels. In essence, enhanced levels of social capital increases the risk of being caught hence reduces the incentive to commit crime.

Unfortunately, as far as we are aware, the important notions of "civic community," "collective efficacy" and "informal control" briefly outline above have not been formally introduced into the rational choice framework. As currently structured, higher levels of social capital is interchangeably with civic engagement. Although outside the scope this applied study, social capital augmented rational choice theories need to be refined to think in terms of engagement.

An anomie-type interpretation could also be inferred from these social capital augmented rational choice theories. If social capital is high within a community one could argue that there higher levels of positive peer pressure thus raising the moral threshold of the potential criminal; the ends do not necessarily justify the means. Within the rational choice framework going against one's moral values would be interpreted as a cost of committing the crime. Alternatively, higher levels of individual frustration through not achieving individual goals may cause one to question their moral position in committing crime. If the social capital of the community is low or deteriorating couple with frustration and/or envy, an individual person's moral threshold may be lowered thus lowering the personal cost of committing a crime.

What is important here from a model uncertainty perspective is how the three theories overlap. Common to all three are social capital and community norms, specifically disruptions in social capital and norms, along with limited economic opportunities such as high levels of poverty or chronic unemployment and high and/or raising levels of inequality. This convergence of theoretical perspectives should reduce model uncertainty. Unfortunately, the empirical literature is still rife with inconsistencies. For example some studies have found that higher levels of average income tend to be associated with lower levels of crime (e.g., Reilly and Witt 1996; Gould, Weinberg and Mustard 2002; Authors) yet others find the opposite (e.g., Rephann 1999; Fajnzylbwe, Lederman and Loayza 2002; Mazerolle, Wickes and McBroom 2010).Income distribution has been a major focus of studies on crime (e.g., Kennedy, et al 1998; Kelly 2000; Carcach2000, 2001; Thorbecke and Charumilind 2002; Pratt and Godsey 2003) and is widely included as a control variable (e.g., Lederman, Loayza and Menendez 2002; Fajnzylber, Lederman and Loayza 2002;Baumer and Gustafson 2007; Li 2009; Authors) but again the results tend to be inconsistent (Fowles and Merva 1996). In a review of sixty empirical studies of crime Chiricos (1987) found that unemployment rates are a strong predictor of property crimes but had a poor relationship to violent crimes. More current work, such as Carcach (2000, 2001), Authors (), Gould, Weinberg and Mustard (2002) and Reilly and Witt (1996) confirm these general results but others such as Timbrell (1990), Field (1990), Pyle and Deadman (1994) and Bausman and Goe (2004) have not been able to confirm this relationship.

From this brief review of the core theoretical perspectives upon which most of the ecological empirical literature is based, model uncertainty can come from three sources. First, the theories basically conclude that everything matters in understanding crime. The resulting laundry list of potential control variables is almost by its very nature a definition of model uncertainty. Second, while many of the concepts behind the drivers of crime may be more or less easily describe, how the concepts are empirically measured is vague which leads to another type of model uncertainty. Third, results have been shown to vary across different types of crime introducing a third layer of model uncertainty. As outlined in the introductory comments, model averaging methods, have been suggested as a superior alternative to traditional model selection methods to address model uncertainty.

Bayesian Model Averaging[3]

In a nutshell standard statistical practices ignore model uncertainty. As described above the most common form of model uncertainty is generally dealt with by the use of a family of model selection methods such as equation F statistic, $\bar{R}^2$ or Mallows' C_p ,Amemiya criteria (PC), Akaike Information Criteria (AIC), Sawa Bayesian Information Criterion and/or the Schwarz Bayesian Information Criterion (BIC). Or, even more crudely, a process of elimination based on individual variable *t* statistics.Analysts typically select a model from some class of models then proceed as if the model generated the data. In addition to problems of vague theoretical foundations for selecting one method over another, critical values of these model selection methods, or rules to follow when methods provide inconsistent results, ignores a component of uncertainty leading to an increase in Type I error and/or over-confident inferences. In the case of a relatively large number of potential variables this can be a very cumbersome and time consuming process.

As an alternative the notion of model averaging has been introduced as a replacement for what can best be described as*ad hoc* model selection approaches. For illustrative purposes suppose that there are three variables (k=3) that are under considerationyielding eight potentialmodels ($M_1 \ldots M_8$ or 2^3)

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[3] This discussion draws on the presentations of Hoeting, Madigan, Raftery and Volinsky (1999), Raftery, Painter and Volinsky (2005), authors () and LeSage and Parent (2007).

	β_1	β_2	β_3
M_1	1	1	1
M_2	0	1	1
M_3	0	0	1
M_4	1	1	0
M_5	1	0	0
M_6	0	1	0
M_7	1	0	1
M_8	0	0	0

Draper (1995) and Wintle, et al. (2003) observation about discrete versus continuous model averaging can be easily seen by how many models (M_i) are explored. Suppose that the analyst predetermines that only models that contain the first variable will be considered (M_1, M_4, M_5 and M_7) then we have a form of discrete model averaging. If all potential models are considered (M_1, …, M_8) then a continuous form of model averaging is being followed.

In the simplest sense model averaging would compute an average value of the estimated parameters, perhaps estimated with least squares, over the eight models: $\overline{\beta_{Mi}} = \sum_{Mi=1}^{8} \omega_{Mi}\beta_{Mi}$ where β_{iM} is the value of the i^{th} parameter for the M^{th}model. The simplest averaging scheme presumes that each model carries the same weight (i.e., ω_{Mi} =1/8). Clearly we can use the statistical strength of each individual mode (M_i) as information in refining the weighting scheme. Hansen (2007) suggests several potential such weighting schemes including $\omega_{Mi} = \frac{\exp\left(-\frac{1}{2}AIC_{Mi}\right)}{\sum_{j=1}^{M}\exp\left(-\frac{1}{2}AIC_{Mj}\right)}$ where AIC is the Akaike Information Criteria or $\omega_{Mi} = \frac{\exp\left(-\frac{1}{2}BIC_{Mi}\right)}{\sum_{j=1}^{M}\exp\left(-\frac{1}{2}BIC_{Mj}\right)}$ where BIC is the Bayesian Information Criteria.

Bayesian model averaging (BMA) has been introduced to provide a coherent mechanism for account for the model uncertainty in terms of what variables should be included in the final specification of the model.Suppose that there is a set of models all of which may be "reasonable" based on the theory for estimating θ from a given data set *y*. Suppose farther that a particular parameter θhas a common interpretation across all possible models $M_1,…,M_k$. Instead of using one single model for making inferences about θ, Bayesian model averaging constructs $\pi(\theta|y)$, the posterior density of θ given the data and is not conditional on any specific model (M_i). Given Bayes formula BMA starts from specifying

- prior probabilities $P(M_j)$ for all models $M_1,\ldots,M_k$ under consideration,
- prior densities $\pi(\theta_j|M_j)$ for all parameters θ_j of the model M_j.

Given the prior information on the parameters for a given model, the integrated likelihood $(L_{n,j})$ of model M_j is given by

$$\gamma_{n,j}(y) = \int [L_{n,j}(y,\theta_j)\pi(\theta_j] \Big| M_j\Big)\, d\theta_j \, .$$

Here $\gamma_{n,j}(y)$ is also the marginal density of the observed data. Using Bayes theorem the posterior density of the model is obtained as

$$P(M_j|y) = \frac{P(M_j)\gamma_{n,j}(y)}{\sum_{j'=1}^{k} [P\left(M'_j]\right)\gamma_{n,j'}(y)}$$

The posterior density of μ for each model is then computed assuming that model M_j is true and is denoted as $\pi(\mu|M_j,y)$. Combining these elements we can express the posterior density of the quantity of interest as

$$\pi(\mu|y) = \sum_{j=1}^{k} P(M_j|y)\pi(\mu|M_j,y)$$

Instead of using a single conditional posterior density $\pi(\mu|M_j,y)$ assuming model M_j to be true, the posterior density $\pi(\mu|y)$ is a weighted average of the conditional posterior densities, where the weights are the posterior probabilities of each model. By not conditioning on any given model, Bayesian model averaging does not make the mistake of ignoring model uncertainty.

The posterior mean is also a weighted average of the posterior means in the separate models, or

$$E(\mu|y) = \sum_{j=1}^{k} P(M_j|y)E(\mu|M_j,y)$$

from properties of the mixture distributions. The posterior variance may be derived from

$$Var(\mu|y) = \sum_{j=1}^{k} P(M_j|y)[Var(\mu|M_j) + \{E(\mu|M_j,y) - E(\mu|y)\}^2]$$

There are several practical difficulties in implementing Bayesian model averaging. The integrals in the integrated likelihood($\gamma_{n,j}(y)$) are hard to compute. The number of terms in the integrated likelihood can be enormous given the potential number of variables to be introduced. For example, if the number of variables included is 10 (k=10) then there are 2^{10}, or 1,024 possible models. Specification of the prior distribution over all the competing models is unclear. Finally, choosing the class of models to average over becomes the fundamental modeling task and there are several competing "schools of thought" (i.e., discrete versus continuous) that have emerged over how to proceed.

As noted in the introductory comments there are at least three potential ways to proceed given the results of the BMA. The first is to examine the full specification using the posterior mean (weighted average of the posterior means in the separate models) coefficient for each variable included in analysis. This approach is most consistent with the intent of BMA to take advantage of the information contained in as many models as possible. Second, focus on the frequency of variables that are included in models that have a posterior probability $(P(M|y))$ greater than some selected threshold, typically one percent. The third and final approached we will examine focuses on the single model with the highest posterior probability to determine which variables are to be further analyzed. The last two methods are more directly filtering processes in the sense that the variables identified as being relevant must be further analyzed in separate regression type analysis (i.e., discrete as opposed to continuous). Thus for the last two methods one could say that the BMA reduces to a two-step process. The BMA is used to select the final set of variables to be used in a second set of analysis.

Magnus, Powell and Prüfer (2010) maintain that these problems with BMA suggest that alternatives such as weighted average lease a squares (WALS) could be considered. First, WALS treats our lack of knowledge about the priors in a more direct manner thus yielding better risk profiles and avoiding unbounded risk in particular. Indeed, the power of a Bayesian approach is that the analyst can use prior information about the underlying model, but in practice we seldom have that prior information in a usable form. Second, as the parameter space (k) raises the computational demands of BMA explodes (2^k) while the computing time of WALS is on an order of k (versus 2^k). Because of the computational demands of BMA Magnus, Powell and Prüfer (2010) correctly point out that exact computational of a complete BMA is seldom carried out. To address these two problems a Markov Chain Monte Carlo (MCMC) method must be used to move the BMA approach forward.

In the application reported here we use the BMA algorithms developed by LeSage and his colleagues (e.g.,LeSage and Parent 2007). Building on the prior work of Raftery, Madigan and Hoeting (1997) as well as Fernandez, Ley and Steel (2001a, 2001b) LeSage adopts a Markov Chain Monte Carlo (MCMC) model composition approach introduced by Madigan and York (1995). Here the process moves through the potentially large model space and sample regions of high posterior support minimizing the need to consider all possible models. Define a neighborhood $nbd(M)$ for each $M \in \mathcal{M}$ (the set of all possible models). Now define a transition matrix q by setting $q(M \rightarrow M') = 0 \ \forall \ M' \notin nbd(M)$ and $q(M \rightarrow M') \neq 0 \ \forall \ M' \in nbd(M)$. If the chain is currently in state M proceed by drawing M' from $q(M \rightarrow M')$. M' is accepted with probability

$$\min\left\{1, \frac{P(M'|y)}{P(M|y)}\right\}.$$

Otherwise the chain remains in state M. Using a Metropolis-Hastings sampling scheme LeSage is able to implement a Markov Chain Monte Carlo routine to move through the modeling space.

As outlined above we explore the drivers of rural crime in the Midwest in three ways using the Bayesian model averaging approach. First, we consider the full specification using the posterior meancoefficients which is closest in intent of the original formulation of BMA. Second, using a posterior probability $(P(M|y))$ greater than one percent we examine the frequency of variable inclusion. For example, if for property crime there are half a dozen potential models that have a posterior probability greater than one percent, how frequently are individual variables contained in those half dozen models. Finally, we use the single model with the highest posterior probability to determine which variables are to be further analyzed. We then take that "final" specification and estimate individual models using simple least squares.

Model Specification

Our variable selection is rooted on our interpretation of the theoretical literature along with the vast empirical literature as well as the modest but growing pool of work on rural crime (e.g., Li 2009; Authors; Lee and Thomas 2010). We hypothesize that the empirical determinants of rural crime can be classified into seven broad categories:

- Scale-Size of the County,
- Income,
- Poverty-Unemployment-Income Distribution,
- Socio-demographic,
- Housing Structure,
- Social-Political Structure,
- Change Characteristics.

Larger communities are more likely to experience higher rates of crime along with those communities that have lower levels of income as well as higher levels of unemployment. Communities that tend to have a larger share of youth will tend to have higher crime while communities with an older population will have less crime. Communities that have a higher ethnic diversity will tend to see higher levels of crime. Communities with a higher share of people living in their own detached homes will tend to experience lower levels of crime. Communities that are experiencing more rapid change will tend to have higher levels of crime. The social-political structure set of variables includes a measure of social capital defined below along with a set of variables intended to capture the attitudes of local residents including measures to capture the “creative” and “bohemian” classes in the spirit of Richard Florida (2002, 2003).

Individual variables within each group include:

<u>Scale/Size of County</u>

1. Population Density
2. Population
3. Number of Jobs
4. Adjacent to a Metro County
5. Remote Rural County

<u>Income Levels</u>

1. Per Capita Income
2. Earnings Per Job
3. Wage and Salaries per Job

<u>Poverty-Unemployment-Income Distrbution</u>

1. Unemployment Rate 2006
2. Per Capita Unemployment Insurance Income
3. Poverty Rate 2004

4. Per Capita Income from Income Maintenance Programs
5. Gini Coefficient of Income Equality 1999

Socio-demographic

1. Percent of Population Age 15 to 24
2. Percent of Population Age 75 plus
3. Percent of the Population Caucasian
4. Percent of the Population African American
5. Percent of the Population Hispanic
6. Ethnic Diversity Index
7. Percent of those over 25 with a High School Education
8. Percent of those over 25 with a Bachelor's Degree
9. Percent of the Population Foreign Born 2000
10. Percent of the Population Non-English Speakers at Home 2000

Home Structure

1. Percent of Houses Owner Occupied 2000
2. Percent of Households Living in Multiple Unit Housing 2000

Social - Political Structure

1. Creative Class Index 2000
2. Bohemian Class Index 2000
3. Social Capital Index
4. Percent of Voters Voting Republican in 2004 Presidential Election
5. Percent of Voters Voting Democratic in 2004 Presidential Election
6. Per Capita Local Government General Revenues 2002

Change Characteristics

1. Net Migration 2000-2006
2. Percent Change in Per Capita Income
3. Percent Change in Earnings per Job
4. Percent Change in Wages and Salary per Job
5. Percent Change in Number of Jobs
6. Percent Change in the Unemployment Rate 2000-2006
7. Percent Change in Per Capita Unemployment Insurance Income 2000-2007
8. Percent Change in Poverty Rate 2000-2004
9. Percent Change in Per Capita Income from Income Maintenance Programs
10. Percent in Same Household 1995-2000
11. Percent Change in Medicate Payments 2000-2005
12. Percent Change in Gini Coefficient 1989-1999

Most of these variables are self-explanatory except for a few indices that are used.[4] Unless otherwise noted all variables are for 2007 and the change variables are for 2000 to 2007. Notice that several of the variables are very similar and could be viewed as proxies. For example, one might expect per capita income, earnings per job and wage and salary income per job to all be highly correlated and perhaps acceptable substitutes for each other. For all practical purpose this represents a certain form of model uncertainty. Alternative, change in the unemployment rate and changes in per capita unemployment insurance income should also be highly correlated. But if we return to the observation of Chrisholm and Choe (2004) what might appear to be modest changes in variable definitions can alter the empirical results. This speaks to the subtle complexities of the drivers of crime and/or high levels of model uncertainty.

The Ethnic Diversity Index is drawn from Rupasingha, Goetz and Freshwater (2006) and Rupasingha and Goetz (2007) who in turn build on Alesina, Baqir and Easterly (1999) and is an ethnic fractionalization index measuring ethnic diversity in counties. This index measures the probability that two randomly drawn people from a county belong to different ethnic groups. The Diversity Index $= 1 - \sum_{i=1}^{n} \tau_i^2$ where τ is the share of population self-identified as a specific ethnic group $i \in I =$ (Caucasian, African-American, Hispanic, Asian, Native American, other). Based on social disorganization theory the greater the ethnic diversity the higher the potential for crime.

The Creative Class Index follows from the work of Richard Florida as interpreted by David McGrahanan at USDA ERS.[5] Florida speaks in terms of the role of professions in what he calls the "creative class" in endogenous innovative growth. Communities with a higher share of employment in the "creative class" increases the likelihood of have people that embody Schumpeter's innovative entrepreneur who are essential to economic growth. McGrahanan uses detailed occupational data from the 2000 Census to build a Creative Class Index for U.S. counties. Occupations included in the Index include executives, financial officers, computer specialist and mathematicians to name just a view. We maintain that if Florida is correct, one would expect to see lower crime rates in communities that have a higher share of occupations composing the Creative Class.

The Bohemian Class Index follows in the spirit of the Creative Class Index and attempts to capture what Wojan, Lambert and McGranahan (2007) refer to as the "creative mllieu". By focusing on the "artisan class" of workers Wojan and his colleagues focus attention on a more narrow definition of Florida's creative class. The "Bohemians" (visual, applied and performing artists and authors) do not include computer scientists or marketing executives but rather people who wish to experiment and be creative in other mediums. Wojan, Lambert and McGranahan (2007 p712) suggest that "[i]f creative people are in fact attracted to creative places, then the location decisions of artists should reveal these preferences." The Bohemian Class Index mirrors the Creative Class Index by using occupational data but focuses on artisans. As with the Creative Class Index, we expect rural counties that have higher concentrations of Bohemians to have lower overall levels of different types of crime.

The Social Capital Index draws from the work of Authors () who in turn build on the work ofRupasingha, Goetz and Freshwater (2006) and Rupasingha and Goetz (2007). Data on organizations that either directly contribute to social capital or serve as proxies for engaged citizens who define social capital at the local level. Data are drawn from four sources: County Business Patterns, the National Center for Charitable Statistics for non-profits, Association of Religion Data Archives for number of churches, synagogues and

[4] Note that there are 43 variables included here. Hence k=43 and the potential number of models that could be estimated is 8,796,093,022,208. Now expand to consider seven different categories of crime ($7x2^{43}$). The observation of Magnus, Powell and Prüfer (2010) strikes home in terms of computational demand; clearly without the Markov Chain Monte Carlo approach, the computational challenges would be almost insurmountable.

[5] See http://www.ers.usda.gov/Data/CreativeClassCodes/methods.htm for details and to view the Index.

mosques within a community and a new data set on cooperative business enterprises compiled by the University of Wisconsin Center for Cooperatives. The one common metric across all four sources is a simple count of the number of organizations. Hence, our metric is a simple summation of a selected number of different types of organizations that contribute to social capital all on a per one thousand persons basis. Clearly a simple head count of different organizations masks the size or scale of individual organizations. We could proxy firms by employment size, or non-profits based on financial data from their IRS 990 filing data and churches by membership size, the heterogeneity across different scale metrics makes building a scalar index difficult.

The specific types of organizations include:

- Business, Professional and Labor Organizations per 1K Persons
- Civic and Social Organization per 1K Persons
- Number of Churches per 1K Persons
- Number of Non-Agricultural Cooperatives per 1K Persons
- Num ber of Non-Profits Public and Social Advocacy Organizations per 1K Persons
- Number of Non-Profit Sports Organizations per 1K Persons
- Number of Non-Profit Youth Organizations per 1K Persons
- Number of Non-Profit Community Development Organizations per 1K Persons

By construction, the higher the number of these types of organizations we argue is associated with higher levels of social capital and in turn lower crime rates.

Despite serious limitations that have been widely discussed in the literature (e.g., Lott and Whitley 2003) the FBI Unified Crime Reports is the best data for rural crime that is available in the U.S. and is widely used to inform and craft policy. This study follows other ecological studies of rural crime patterns and use the UCR data (e.g., Wilkinson 1984a, 1984b; Petee and Kowalski 1993; Mencken and Barnett 1999; Rephann 1999; Osgood and Chambers 2000; Barnett and Mencken 2002; Lee and Bartkowski 2004; Bouffard and Muftic 2006; Authors, 2007; and Li 2009). We do not model aggregate violent and property crime rates because it has been suggested within the literature that these measures introduce aggregation bias into the analysis. Rather we model murders, forcible rapes, robberies, assaults, burglary, larceny and motor vehicle rates (number of incidents dividend by population adjusted to 10,000 persons) using an average of annual crime data for 2008, 2007 and 2006. By taking an average any unusual spikes in the annual crime data are removed, particularly for violent crime. Once missing data is accounted for the final sample size is 314 rural counties in the U.S. Midwest. Much of the missing data comes from gaps in the FBI UCR reports.

Empirical Results

There are three sets of results to be discussed. The first is the full specification using the posterior mean (weighted average of the posterior means in the separate models) coefficient for each variable included in our set of variables (i.e., continuous). Second, we identify the frequency of variables that are included in models that have a posterior probability greater than one percent. We elected to retain only those variables that appeared in each model that met the one percent threshold (i.e., discrete). Finally, we use the single model with the highest posterior probability to determine which variables are to be further analyzed (i.e., discrete). For reporting each of the three set of results are reported by the seven types of crime analyzed here. For the weighted average of the posterior means results we report only those variables that had a significance level of 90 percent or higher. The full results for the full specification with the posterior means along with the full frequency analysis are provided in an Appendix to the study.

Violent Crime Consider first the results for the murder rate (Table 1). Of the 43 variables that are examined only four are consistently identified by the BMA approach as important to rural murder rates in the Midwest: population density, per capita unemployment insurance, percent of the population Caucasian and the social capital index. Two of the results are somewhat surprising, higher population densities and unemployment insurance payments in Midwestern rural counties are associated with lower murder rates. These two results are unexpected because the common theoretical understanding is that higher population density creates greater opportunities for conflict and crime. At the same time per capita unemployment insurance income is an alternative measure of unemployment which should be associated with higher crime, but for the rural Midwest and murder rates the opposite appears to hold. Interestingly the ethnic diversity index, which is the most consistent metric with respect to the theoretical frameworks outline above, does not appear to influence the rural murder rates, but a higher share of the county population that is Caucasian is associated with lower murder rates. But at the same time the percent of the population that is African-American or Hispanic does not enter into the analysis. The most interesting result is the negative influence social capital, proxied by our Social Capital Index, has on rural crime rates. This result is most consistent with theory.

Only two other variables appear to have some role in explaining Midwestern rural murder rates: earnings per job, which is one of several variables potential measures of income, and the percent of households living in multi-family developments. Here again, both variables have relationships with murder rates opposite what we expected given the theory. One would expect higher income levels would be associated with lower crime, murder in this case, but the data suggests the opposite holds. Following the same logic as population density we expected that more people living in compacted areas, such as multi-family residential developments like apartment buildings, would increase conflict and crime. The rural data supports the opposite. Three other variables that are in the highest posterior probability model are not statistically significant when the final model is estimated via least squares. Finally, the percent of variance in the rural crime rate is relatively low ranging from about 12 to 18 percent, but this is fairly consistent with other studies examining the murder rate.

Rape is generally very difficult to model empirically because of the nature of the crime. But for the Midwestern rural data, the BMA approach identified several potential drivers of rape (Table 2).Based on the R^2 the percent variation in rural rape explained by the three BMA derived models range from 21 to 33 percent. There are seven variables that are consistently identified as associated with rural rape: per capita income from income maintenance programs, percent of the population that is Caucasian, percent of those over the age of 25 with a high school education, percent change in Medicare payments, percent of houses that are owner occupied, percent change in the gini coefficient of income equality and the dummy variable if the county is adjacent to a metro area. It is important to note that the stability of statistical significance for percent of the population Caucasian and the metro adjacency dummy variable is weak across the three specifications suggesting that these two results are tenuous at best.

What is interesting here is that higher levels of all these seven variables are positively related to rural rape rates. These positive relations is as expected given the theory for per capita income from income maintenance programs, a proxy measure for poverty, and increases in income inequality (rising gini coefficients) and perhaps the adjacency to metro areas.It is interesting to note that the poverty rate is identified by two of the ways to interpret the BMA approach (i.e., the highest posterior probability as well as the highest frequency interpretations) but when the models are estimated with least squares poverty rate becomes statistically insignificant. It is not clear why rural counties in the Midwest with higher home owner occupancy rates, education rates measured by high school education, or increases in Medicare payments would be associated with higher rates of rape. Other variables that were also identified by one of the three ways to use the results of the BMA approach include percent change in earnings per job, percent change in number of jobs, and change in the unemployment rate. The first two could be interpreted as metrics of economic growth and higher levels are associated with higher rates of rape. Increases in the unemployment rate also appears to be associated with higher rates of rape and this result is consistent with theory but the unemployment rate by itself does not appear to influence rape.

The results for rural Midwestern robberies are presented in Table 3. Out of 43 potential variables only one variable appears in all three interpretation of the BMA analysis: percent of income from income maintenance programs, a proxy or alternative measure of poverty. Higher levels of payments from these programs are associated with higher rates of robbery which is consistent with theoretical expectations. Only one other variable appears to be related to rural robberies, net migration but in a direction that is not consistent with theoretical expectations. One would expect that counties experiencing higher levels of net migration (i.e., net in-migration) would experience changes in the social structure of the community resulting in conflict and increases in crime. The data do not support this interpretation.

The results for the final category of violent crime examined, assaults, are presented in Table 4. Percent of the variation in assaults explained ranges from about 33 to 37 percent, again using the R^2, which is consistent with most studies of rural crime rates. Six variables are consistently found to influence Midwestern rural assault rates: percent change in per capita income, earnings per job, percent of the population between the age of 15 and 24, residential stability measured by percent of households in the same house between 1995 and 2000, as well as the percent of households living in multi-unit housing developments and per capita local government general revenues. Changes in per capita income tends to be associated with higher levels of assaults but higher levels of each of the other five variables are all tied to lower levels of rural assaults. This result is consistent with theory in terms of earnings per jobs and residential stability, but the youth measure and multi-unit living arrangements are not consistent with theory.

There are three additional variables that are identified in the highest posterior probability model that are statistically significant via the least squares estimated assaults model. These include percent of the population over age 75, percent of the population that is Caucasian and the Ethnic Diversity Index with each having a negative estimated coefficient. The result for an older population is as expected but the result for ethnic diversity is unexpected. Social disorganization theory suggests that higher ethnic diversity heightens the potential for conflict and hence crime. For the rural Midwest this does not appear to be the case. This latter result coupled with the negative influence a higher share of the population that is Caucasian has on assaults suggest that ethnicity plays a complex role that is not being cleanly captured by our measures.

Several conclusions can be drawn from these results on the four components of violent crime examined here. First, given that we introduced 43 separate variables into the analysis only a small handful of variables are consistent with the rural violent crime data. Many socioeconomic characteristics that theory predicts should be important determinants of violent crime tend to play a secondary role. The theoretical perspective that “everything matters” can be challenged based on these results, at least for rural violent crime in the Midwest. Second, there is very little overlap in the relevant variables across the four difference types of violent crime. Thus, what appears to drive one type of violent crime does not necessarily drive other types of violent crime. This also suggests that attempts to model total violent crime may introduce aggregation bias into the analysis. Finally, the numerous results are not consistent with theoretical predictions. This speaks less to the relatively few variables that are consistently help explain the underlying data but more to the direction (negative or positive) of the relationship.

Property Crime Consider first the burglary rate for Midwestern rural counties (Table 5). The R^2 ranges from 0.2894 to 0.3419 which means that the models explains about a third of the variation in burglary rates. Six variables are consistent across all three ways to interpret the BMA approach: change in the poverty rate, percent of the population between the ages of 15 and 24, residential stability, percent of households living in multi-unit housing developments, change in income inequality and social capital. Three of the variables have directional relationships with burglary rates that are consistent with theory. For example,a higher level of social capital as measured by our Index is associated with lower burglary rates as is residential stability. In addition, rising levels of income inequality are associated with higher burglary rates. Theory tells us that increases in poverty should be linked to higher crime, but the data suggests the opposite; increases in the poverty rateare tied to lower burglary rates. Theory would also suggest that higher concentrations of people living in close proximity, such as multi-unit residential developments, should increase the likelihood of conflict and crime. But the rural data examined in this study suggests the opposite is true. There is also some evidence that growth in earnings per job will lower burglary rates which is consistent with theoretical expectations.

Finally, there is again some evidence that a larger share of the population that speaks a language other than English at home is associated with lower burglary rates. This latter result is not consistent with what theory would suggest. In the same line as ethnic diversity theory would suggest that more people that either do not speak English or English is a second language should create more opportunities for conflict and crime. But the rural data does not this line of thinking. This result is particularly important to the rural Midwest where there is a growing Hispanic population. A widely held concern is that the growth in the Hispanic population is placing upward pressure on crime. But this latter empirical result coupled with the lack of the share of the population that is Hispanic entering into any type of crime models challenges this perception.

The larceny results for the rural Midwest are provided in Table 6. Based on the R^2 the models explain between about one-quarter and one-fifth of the variation in larceny rates. There are only two variables that are consistently identified by the BMA approach; percent change in the number of jobs which has a positive impact on larceny rates and percent of households living in multi-unit developments which has a dampening effect. Other variables identified by two of the three ways to interpret the BMA results include population density which has a positive impact on larceny which is consistent with theory as well as income from income maintenance programs, a proxy for poverty, and increases in income inequality also raised larceny rates. These latter three results are consistent with theoretical expectations.

The final category of rural crime examined is motor vehicle thefts and results are presented in Table 7. As with most of the other crime models between one-quarter and one-fifth of the variation in motor vehicle thefts is explained by the BMA derived models. There are four variables identified including change in the unemployment rate, share of population African-American, residential stability and multi-unit housing developments. Each of the four variables has negative coefficients and for residential stability this is as expected. Increasing unemployment rates along with more compact living arrangements via multi-unit residential developmentsshould place upward pressure of thefts but the rural data supports the opposite. Other variables that are identified by the highest posterior probability and highest frequency models, such as the two age profile variables, tend to be statistically insignificant when estimated using least squares.

As with violent crime it is somewhat surprising that only a small handful of variables influence rural crime property crime rates in the Midwest. Two variables that are consistent predictors of rural crime are residential stability and multi-unit residential living. Theory tells us that increased residential stability should have a dampening effect on crime and the data supports that concept. But theory tells us that people living in more compact settings, such as apartment complexes, should increase the likelihood of conflict and hence crime, but the rural data does not support this notion. Rather more households living in multi-unit develops appears to dampen crime. It may be the case that people living for extended periods of time in the same multi-unit residential develop build a stronger sense of community within the development and this places downward pressure on crime.

There is some evidence that increases in income inequality places upward pressure on crime, as predicted by the theory, and while poverty in and of itself does not appear to influence rural property crime there is some evidence that higher levels of dependency on income from income maintenance programs, an alternative measure of poverty, does place upward pressure on crime. Also contrary to what theory might predict, a higher concentration of young adults (ages 15 to 24) is not associated with higher levels of property crime, but indeed may be associated with lower levels of rural crime.

Conclusions

There are three problems facing the empirical criminology literature. First the theory basically concludes that "everything matters" when trying to understand crime patterns. Second, the empirical results are very sensitive to how key variables are measured. For example, the theories tell us that income matters, but how one measures income can have significant impacts on the empirical results. If one finds empirical evidence supporting the theory using one measure of income, then finds contradictory evidence using a slightly different measure of income, where does that leave us and more importantly where does that leave policy options.Third, while "empirical truths" are far and few between what appears to hold for urban does not hold for rural. Are rural and urban so fundamental different that we need distinct and separate theoretical and empirical frameworks?

From the perspective of empirical modeling the criminology literature is fraught with model uncertainty. Model uncertainty exists when theory tells us that "everything matters", theory produces a "laundry list" of potential control variables, or there are multiple ways to measure a particular characteristics and theory provides no insights in how to proceed. Model uncertainty can be a particular problem when a truly interdisciplinary approach is taken to study a problem as within the field of criminology. One approach that is gaining favor as an alternative to traditional model selection methods is model averaging.In this study we follow the lead of Bruce Western (1996, 2001) and suggest that Bayesian model averaging (BMA) might be one empirical approach to help us systematically tackle the problem of model uncertainty.

Based on our analysis we find that a common set of variables tend to drive most types of rural crime including stability in housing residency, living in multi-unit housing development, changes in poverty, changes in income inequality,social capital and youth concentrations. But the empirical relationships are not always consistent with theory or across different types of crime. For example, theoretically increases in the poverty rate should place upward pressure on crime. The data for the rural Midwest suggests the opposite is true. Surprisingly, the one variable that tended to dominate the analysis is not something one would expect from the theory: living in multi-unit housing development. At first glance the theory might suggest that the higher this percentage the higher the crime rate; such housing is generally associated with lower levels of wealth, more opportunities to commit crime and higher concentrations of people living in close proximity increasing the likelihood of conflict. But the data consistently suggests that the higher the percent of households living in multi-unit developments the lower the crime rate across several different types of crime. Could it be that in rural areas these types of living arrangements makes for a stronger sense of community (a form of social capital) and the likelihood of formal or informal neighborhood watch efforts. For example, is a thief more likely to steal from a condo located in a higher concentration of other condos or a remote house isolated on 20 acres?

A somewhat surprising result is the relatively small number of variables that are consistent with the underlying data generating process. While the model derived with the highest posterior probability tends to have a range of variables included, the full specification using the posterior mean coefficients, which is closest in intent of the original formulation of BMA, tended to have very few variables and in the case of robberies only one variable. For the rural Midwest data the theoretical conclusion that "everything matters" does not seem to apply.

The variation in variables introduced into the different types of crime models is an important result. One of the criticisms of much of the earlier empirical work is aggregation bias in how crime is defined and the results here confirm that criticism. As discussed above, there is some overlap in terms of a core set of variables that enter the models, there is significant differences in the underlying data generating process for different types of violent and property crime. Our results suggest that care must be taken in how researchers define crime.

There are at least two next steps for this work. First, it is generally accepted in the ecological criminology literature that there is spatial dependency in the underlying data generating process (i.e., the third source of model uncertain identified by Western (1996), the stochastic process). Such dependency is ignored in this analysis. Using spatial estimators such as those suggested by LeSage and Parent (2007) is a logical next step. Alternative a spatial corrected weighted least squares building on the work of Hansen (2007) might be a potential next step. Second, the data analyzed here is limited to the rural Midwest. There is sufficient evidence in the literature that there could be significant spatial heterogeneity in the drivers of rural crime. In other words are the findings for the rural Midwest transferable to the Mississippi Delta or the Mountain West? Expanding the study area to include nonmetro counties for all the lower 48 states is a natural next step.

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Table 1: Bayesian Model Averaging Results for Midwestern Rural Murder Rates

	Bayesian	Highest Posterior Probability (OLS)	Highest Frequency (OLS)
Population Density	-0.00008	-0.00007	-0.00012
	(0.0921)	(0.0831)	(0.0019)
Per Capita Unemployment Insurance Income	-0.00006	-0.00006	-0.00006
	(0.0081)	(0.0033)	(0.0003)
Percent of the Population Caucasian	-0.00067	-0.00080	-0.00078
	(0.0448)	(0.0115)	(0.0121)
Social Capital Index	-0.00469	-0.00455	-0.00396
	(0.0019)	(0.0023)	(0.0067)
Earnings Per Job	–	0.00000	0.00000
		(0.0352)	(0.0013)
Percent Change in Per Capita Unemployment Insurance Income 2000-2007	–	-0.00303	–
		(0.2981)	
Creative Class Index 2000	–	-0.06227	–
		(0.1712)	
Percent of Population Age 75 plus	–	-0.00042	-0.00064
		(0.6097)	(0.4346)
Percent of Households Living in Multiple Unit Housing 2000	–	-0.00055	–
		(0.0793)	
R^2	0.1777	0.1394	0.1224
$F_{statistic}$	–	6.47	8.07
Number of Models	9,256	–	–

t-test probability in parentheses

Table 2: Bayesian Model Averaging Results for Midwestern Rural Rape Rates

	Bayesian	Highest Posterior Probability (OLS)	Highest Frequency (OLS)
Per Capita Income from Income Maintenance Programs	0.00015	0.00015	0.00016
	(0.0117)	(0.0140)	(0.0093)
Percent of the Population Caucasian	0.00420	0.00377	0.00293
	(0.0719)	(0.1080)	(0.2109)
Percent of those over 25 with a High School Education	0.00345	0.00377	0.00339
	(0.0053)	(0.0019)	(0.0054)
Percent Change in Medicare Payments 2000-2005	0.00293	0.00282	0.00328
	(0.0168)	(0.0279)	(0.0083)
Percent of Houses Owner Occupied 2000	0.00265	0.00269	0.00251
	(0.0608)	(0.0560)	(0.0734)
Percent Change in Gini Coefficient 1989-1999	0.14301	0.16383	0.18576
	(0.0575)	(0.0304)	(0.0125)
Adjacent to a Metro County	0.08704	0.00387	0.00537
	(0.0078)	(0.7059)	(0.6035)
Percent Change in Earnings per Job	–	0.09265	–
		(0.0749)	
Wage and Salaries per Job	–	0.00000	–
		(0.2084)	
Percent Change in Number of Jobs	–	0.13344	–
		(0.0684)	
Unemployment Rate 2006	–	0.00524	0.00100
		(0.2976)	(0.8305)
Percent Change in the Unemployment Rate 2000-2006	–	0.06407	0.05367
		(0.0064)	(0.0144)
Poverty Rate 2004	–	0.00341	0.00325
		(0.5032)	(0.5192)
Percent of the Population African American	–	0.00506	0.00457
		(0.1291)	(0.1735)
Gini Coefficient of Income Equality 1999	–	0.45021	0.57941
		(0.2709)	(0.1160)
R^2	0.2908	0.3332	0.2131
$F_{statistic}$	–	14.81	7.86
Number of Models	8,990	–	–

t-test probability in parentheses

Table 3: Bayesian Model Averaging Results for Midwestern Rural Robbery Rates

	Bayesian	Highest Posterior Probability (OLS)	Highest Frequency (OLS)
Per Capita Income from Income Maintenance Programs	0.00008	0.00011	0.00010
	(0.0022)	(0.0002)	(0.0004)
Net Migration 2000-2006	–	-0.00003	-0.00003
		(0.0206)	(0.0250)
Percent Change in Earnings per Job	–	-0.04026	-0.02790
		(0.1056)	(0.2204)
Unemployment Rate 2006	–	-0.00231	–
		(0.1965)	
Poverty Rate 2004	–	-0.00245	-0.00204
		(0.0962)	(0.1615)
Percent of Population Age 75 plus	–	-0.00222	-0.00370
		(0.2127)	(0.0239)
Percent of the Population Caucasian	–	-0.00119	–
		(0.0995)	
Percent of Voters Voting Democratic in 2004 Presidential Election	–	-0.00040	–
		(0.2045)	
Social Capital Index	–	-0.00282	-0.00093
		(0.3936)	(0.7647)
R^2	0.1766	0.1368	0.131
$F_{statistic}$	–	6.35	8.64
Number of Models	7,704	–	–

t-test probability in parentheses

Table 4: Bayesian Model Averaging Results for Midwestern Rural Assault Rates

	Bayesian	Highest Posterior Probability (OLS)	Highest Frequency (OLS)
Percent Change in Per Capita Income	1.99687	2.13215	2.08438
	(0.0000)	(0.0001)	(0.0001)
Earnings Per Job	-0.00002	-0.00002	-0.00002
	(0.0089)	(0.0051)	(0.0005)
Percent of Population Age 15 to 24	-0.04458	-0.04626	-0.03718
	(0.0009)	(0.0005)	(0.0031)
Percent in Same Household 1995-2000	-0.05541	-0.05357	-0.05678
	(0.0000)	(0.0001)	(0.0001)
Percent of Households Living in Multiple Unit Housing 2000	-0.02223	-0.01882	-0.02666
	(0.0248)	(0.0519)	(0.0022)
Per Capita Local Government General Revenues 2002	-0.00015	-0.00015	-0.00014
	(0.0007)	(0.0010)	(0.0007)
Population Density	–	-0.00184	–
		(0.1306)	
Percent of Population Age 75 plus	–	-0.04252	–
		(0.0784)	
Percent of the Population Caucasian	–	-0.02462	–
		(0.0859)	
Ethnic Diversity Index	–	-1.29962	–
		(0.0745)	
Percent of Voters Voting Republican in 2004 Presidential Election	–	-0.00249	–
		(0.9827)	
Percent of Voters Voting Democratic in 2004 Presidential Election	–	-0.00237	–
		(0.9837)	
Adjacent to a Metro County	–	-0.03232	-0.04414
		(0.6411)	(0.4839)
R^2	0.3707	0.3371	0.3325
$F_{statistic}$	–	12.89	22.63
Number of Models	8,699	–	–

t-test probability in parentheses

Table 5: Bayesian Model Averaging Results for Midwestern Rural Burglary Rates

	Bayesian	Highest Posterior Probability (OLS)	Highest Frequency (OLS)
Percent Change in Earnings per Job	-1.59109	-2.20799	–
	(0.0934)	(0.0150)	
Percent Change in Poverty Rate 2000-2004	-2.21695	-2.17807	-2.01143
	(0.0038)	(0.0034)	(0.0074)
Percent of Population Age 15 to 24	-0.09230	-0.09230	-0.10664
	(0.0312)	(0.0339)	(0.0153)
Percent in Same Household 1995-2000	-0.05525	-0.05355	-0.05522
	(0.0275)	(0.0293)	(0.0210)
Percent of Households Living in Multiple Unit Housing 2000	-0.09696	-0.09496	-0.09414
	(0.0005)	(0.0006)	(0.0007)
Percent Change in Gini Coefficient 1989-1999	5.65255	5.70870	5.73684
	(0.0000)	(0.0001)	(0.0001)
Social Capital Index	-0.38715	-0.38988	-0.43602
	(0.0010)	(0.0008)	(0.0002)
Per Capita Unemployment Insurance Income	–	-0.00295	-0.00180
		(0.0603)	(0.2280)
Percent of Population Age 75 plus	–	-0.08630	-0.07948
		(0.2331)	(0.2517)
Percent of the Population African American	–	-0.04163	–
		(0.2289)	
Percent of those over 25 with a Bachelor's Degree	–	-0.02731	-0.01891
		(0.3609)	(0.5224)
Percent of the Population Non-English Speakers at Home 2000	–	-0.05382	–
		(0.0399)	
R^2	0.3419	0.3108	0.2894
$F_{statistic}$	–	12.42	14.76
Number of Models	7,894	–	–

t-test probability in parentheses

Table 6: Bayesian Model Averaging Results for Midwestern Rural Larceny Rates

	Bayesian	Highest Posterior Probability (OLS)	Highest Frequency (OLS)
Percent Change in Number of Jobs	5.97350	9.62130	9.80829
	(0.0156)	(0.0001)	(0.0001)
Percent of Households Living in Multiple Unit Housing 2000	-0.17978	-0.19342	-0.18488
	(0.0007)	(0.0002)	(0.0001)
Population Density	–	0.02048	0.02153
		(0.0016)	(0.0004)
Unemployment Rate 2006	–	0.11897	0.18544
		(0.4240)	(0.1296)
Per Capita Income from Income Maintenance Programs	–	0.00283	0.00240
		(0.0110)	(0.0278)
Percent Change in Medicare Payments 2000-2005	–	0.02769	–
		(0.5200)	
Per Capita Local Government General Revenues 2002	–	0.00049	–
		(0.0451)	
Percent of Voters Voting Republican in 2004 Presidential Election	–	0.02489	–
		(0.2962)	
Percent Change in Gini Coefficient 1989-1999	–	6.26539	5.84722
		(0.0228)	(0.0331)
Remote Rural County	–	1.27046	1.24915
		(0.2834)	(0.2923)
R^2	0.2497	0.2011	0.1962
$F_{statistic}$	–	8.65	11.60
Number of Models	6,989	–	–

t-test probability in parentheses

Table 7: Bayesian Model Averaging Results for Midwestern Rural Motor Theft Rates

	Bayesian	Highest Posterior Probability (OLS)	Highest Frequency (OLS)
Percent Change in the Unemployment Rate 2000-2006	-0.21475	-0.23547	-0.30299
	(0.0125)	(0.0049)	(0.0001)
Percent of the Population African American	-0.02658	-0.02200	-0.01672
	(0.0116)	(0.0093)	(0.0433)
Percent in Same Household 1995-2000	-0.01758	-0.01635	-0.01976
	(0.0029)	(0.0049)	(0.0002)
Percent of Households Living in Multiple Unit Housing 2000	-0.01899	-0.01716	-0.02335
	(0.0054)	(0.0065)	(0.0001)
Net Migration 2000-2006	–	-0.00015	–
		(0.1919)	
Percent of Population Age 15 to 24	–	-0.01382	-0.01482
		(0.1342)	(0.0782)
Percent of Population Age 75 plus	–	-0.02885	-0.01679
		(0.1030)	(0.2902)
Percent of those over 25 with a High School Education	–	-0.00913	-0.00904
		(0.1643)	(0.0596)
Percent of the Population Non-English Speakers at Home 2000	–	-0.01018	–
		(0.1433)	
Per Capita Local Government General Revenues 2002	–	-0.00004	-0.00005
		(0.1624)	(0.0892)
Gini Coefficient of Income Equality 1999	–	-0.86147	–
		(0.4269)	
Social Capital Index	–	-0.04038	-0.03279
		(0.1299)	(0.1898)
R^2	0.2659	0.2246	0.2115
$F_{statistic}$	–	8.34	10.06
Number of Models	8,808	–	–

t-test probability in parentheses

Appendix Table 1: BMA Posterior Estimates Midwest Rural Violent Crime

	Murder		Rape		Robbery		Assault	
Constant	0.24539	(0.0000)	-1.37639	(0.0034)	0.15490	(0.0206)	7.57243	(0.0000)
Population Density	***-0.00008***	***(0.0921)***	0.00003	(0.8698)	0.00000	(0.9913)	-0.00132	(0.2769)
Net Migration 2000-2006	0.00000	(0.9406)	0.00000	(0.9999)	-0.00002	(0.2643)	-0.00001	(0.9729)
Population	0.00000	(0.9679)	0.00000	(0.9729)	0.00000	(0.9584)	0.00000	(0.9947)
Per Capita Income	0.00000	(0.9729)	0.00000	(0.9892)	0.00000	(0.9877)	0.00000	(0.9970)
Percent Change in Per Capita Income	-0.00380	(0.8366)	0.02238	(0.7618)	-0.00455	(0.9036)	***1.99687***	***(0.0000)***
Earnings Per Job	0.00000	(0.1052)	0.00000	(0.9673)	0.00000	(0.9450)	***-0.00002***	***(0.0089)***
Percent Change in Earnings per Job	-0.00439	(0.7428)	0.02398	(0.6413)	-0.02241	(0.4496)	0.00427	(0.9924)
Wage and Salaries per Job	0.00000	(0.9570)	0.00000	(0.4232)	0.00000	(0.9655)	0.00000	(0.9704)
Percent Change in Wages and Salary per Job	0.00004	(0.9985)	0.05009	(0.5013)	-0.00860	(0.8174)	0.00050	(0.9992)
Number of Jobs	0.00000	(0.9746)	0.00000	(0.9797)	0.00000	(0.9938)	0.00000	(0.9826)
Percent Change in Number of Jobs	-0.00031	(0.9858)	0.06965	(0.3372)	-0.00022	(0.9949)	0.00053	(0.9991)
Unemployment Rate 2006	-0.00020	(0.8471)	0.00376	(0.4437)	-0.00067	(0.7440)	0.00003	(0.9991)
Percent Change in the Unemployment Rate 2000-2006	0.00003	(0.9973)	0.06276	(0.0054)	-0.00028	(0.9834)	0.00023	(0.9991)
Per Capita Unemployment Insurance Income	***-0.00006***	***(0.0081)***	0.00000	(0.9871)	-0.00001	(0.8147)	-0.00001	(0.9888)
Percent Change in Per Capita Unemployment Insurance Income 2000-2007	-0.00172	(0.5722)	-0.00040	(0.9824)	0.00020	(0.9797)	-0.05196	(0.5103)
Poverty Rate 2004	0.00004	(0.9633)	0.00329	(0.5251)	-0.00126	(0.4356)	0.00062	(0.9808)
Percent Change in Poverty Rate 2000-2004	0.00004	(0.9971)	-0.00038	(0.9928)	-0.00969	(0.6568)	-0.00037	(0.9989)
Per Capita Income from Income Maintenance Programs	0.00000	(0.9869)	***0.00015***	***(0.0117)***	***0.00008***	***(0.0022)***	-0.00004	(0.8953)
Percent Change in Per Capita Income from Income Maintenance Programs	-0.00466	(0.5079)	-0.00003	(0.9993)	-0.00136	(0.9338)	-0.00268	(0.9889)
Creative Class Index 2000	-0.03554	(0.4795)	-0.00029	(0.9991)	0.01408	(0.9225)	0.00418	(0.9977)
Bohemian Class Index 2000	-0.04093	(0.9168)	0.52637	(0.7584)	0.02970	(0.9728)	0.00185	(0.9999)

t-test probability in parentheses

Appendix Table 1 (cont): BMA Posterior Estimates Midwest Rural Violent Crime

	Murder		Rape		Robbery		Assault	
Percent of Population Age 15 to 24	-0.00021	(0.6592)	0.00008	(0.9684)	-0.00038	(0.7257)	***-0.04458***	***(0.0009)***
Percent of Population Age 75 plus	-0.00042	(0.6531)	0.00000	(0.9997)	-0.00272	(0.1438)	-0.03007	(0.2123)
Percent of the Population Caucasian	***-0.00067***	***(0.0448)***	***0.00420***	***(0.0719)***	-0.00095	(0.2000)	-0.01333	(0.3605)
Percent of the Population African American	0.00001	(0.9948)	0.00540	(0.1035)	0.00007	(0.9577)	-0.01150	(0.5652)
Percent of the Population Hispanic	0.00000	(0.9948)	0.00100	(0.6078)	-0.00034	(0.8121)	-0.00951	(0.4567)
Ethnic Diversity Index	0.00007	(0.9977)	0.00617	(0.9540)	0.00192	(0.9911)	-0.21040	(0.7768)
Percent of those over 25 with a High School Education	-0.00007	(0.7939)	***0.00345***	***(0.0053)***	0.00004	(0.9563)	0.00034	(0.9687)
Percent of those over 25 with a Bachelor's Degree	-0.00004	(0.9182)	0.00001	(0.9963)	-0.00014	(0.8758)	0.00051	(0.9627)
Percent of the Population Foreign Born 2000	0.00001	(0.9928)	0.00015	(0.9703)	-0.00052	(0.7791)	-0.00583	(0.8315)
Percent of the Population Non-English Speakers at Home 2000	-0.00001	(0.9791)	0.00000	(0.9982)	-0.00009	(0.9152)	-0.00014	(0.9871)
Percent in Same Household 1995-2000	-0.00004	(0.9070)	0.00000	(0.9986)	0.00003	(0.9639)	***-0.05541***	***(0.0000)***
Percent Change in Medicare Payments 2000-2005	-0.00005	(0.8760)	***0.00293***	***(0.0168)***	-0.00030	(0.6437)	0.00000	(0.9999)
Percent of Houses Owner Occupied 2000	-0.00001	(0.9815)	***0.00265***	***(0.0608)***	-0.00040	(0.6983)	0.00001	(0.9997)
Percent of Households Living in Multiple Unit Housing 2000	-0.00048	(0.1746)	0.00000	(0.9994)	-0.00059	(0.5769)	***-0.02223***	***(0.0248)***
Per Capita Local Government General Revenues 2002	0.00000	(0.9888)	0.00000	(0.9998)	0.00000	(0.9808)	***-0.00015***	***(0.0007)***
Percent of Voters Voting Republican in 2004 Presidential Election	-0.00090	(0.8423)	0.00107	(0.9293)	0.00026	(0.9625)	-0.00664	(0.9539)
Percent of Voters Voting Democratic in 2004 Presidential Election	-0.00092	(0.7971)	0.00092	(0.9626)	0.00008	(0.6201)	-0.00662	(0.9554)
Gini Coefficient of Income Equality 1999	-0.01545	(0.7669)	0.45344	(0.2563)	0.05207	(0.8191)	-0.10212	(0.9460)
Percent Change in Gini Coefficient 1989-1999	-0.00080	(0.9649)	***0.14301***	***(0.0575)***	0.00101	(0.9793)	0.00027	(0.9996)
Social Capital Index	***-0.00469***	***(0.0019)***	0.00000	(1.0000)	-0.00320	(0.3261)	0.00000	(1.0000)
Adjancent to a Metro County	0.00000	(1.0000)	***0.08704***	***(0.0078)***	-0.00013	(0.9939)	0.03841	(0.8528)
Remote Rural County	0.00000	(1.0000)	0.00000	(1.0000)	0.00048	(0.9272)	0.00000	(1.0000)
R^2	0.1777		0.2908		0.1766		0.3707	
Number of Models	9,256		8,990		7,704		8,699	

t-test probability in parentheses

Appendix Table 2: BMA Posterior Estimates Midwest Rural Property Crime

	Burglary		Larceny		Motor	
Constant	2.09281	(0.0006)	-10.98980	(0.1489)	2.92173	(0.0000)
Population Density	0.00004	(0.9929)	0.01060	(0.1294)	0.00001	(0.9899)
Net Migration 2000-2006	-0.00022	(0.6592)	-0.00017	(0.8561)	-0.00011	(0.3583)
Population	0.00000	(0.9984)	0.00000	(0.9914)	0.00000	(0.9888)
Per Capita Income	0.00000	(0.9828)	0.00000	(0.9791)	0.00000	(0.9538)
Percent Change in Per Capita Income	0.00485	(0.9977)	0.00186	(0.9995)	-0.00839	(0.9786)
Earnings Per Job	0.00000	(0.9681)	-0.00001	(0.8540)	0.00000	(0.9853)
Percent Change in Earnings per Job	**-1.59109**	**(0.0934)**	-0.57402	(0.7503)	-0.01049	(0.9603)
Wage and Salaries per Job	0.00000	(0.9968)	-0.00001	(0.9053)	0.00000	(0.9964)
Percent Change in Wages and Salary per Job	-0.67077	(0.6188)	-0.81368	(0.7498)	-0.00001	(1.0000)
Number of Jobs	0.00000	(0.9900)	0.00000	(0.9962)	0.00000	(0.9789)
Percent Change in Number of Jobs	0.00033	(0.9998)	***5.97350***	***(0.0156)***	0.00021	(0.9994)
Unemployment Rate 2006	0.00001	(0.9999)	0.10790	(0.4597)	-0.00015	(0.9931)
Percent Change in the Unemployment Rate 2000-2006	0.00032	(0.9993)	-0.00162	(0.9981)	***-0.21475***	***(0.0125)***
Per Capita Unemployment Insurance Income	-0.00227	(0.1607)	0.00000	(0.9994)	-0.00011	(0.7748)
Percent Change in Per Capita Unemployment Insurance Income 2000-2007	0.00035	(0.9988)	0.00370	(0.9938)	0.00104	(0.9897)
Poverty Rate 2004	-0.00536	(0.9075)	-0.02006	(0.8733)	0.00020	(0.9922)
Percent Change in Poverty Rate 2000-2004	***-2.21695***	***(0.0038)***	-0.52048	(0.7238)	-0.10184	(0.5950)
Per Capita Income from Income Maintenance Programs	0.00000	(0.9998)	0.00233	(0.1074)	0.00000	(0.9991)
Percent Change in Per Capita Income from Income Maintenance Programs	0.00243	(0.9966)	-0.01074	(0.9914)	0.00119	(0.9930)
Creative Class Index 2000	-0.30609	(0.9408)	0.25576	(0.9702)	-0.00136	(0.9984)
Bohemian Class Index 2000	0.02690	(0.9993)	5.69966	(0.9317)	0.00273	(0.9997)

t-test probability in parentheses

Appendix Table 2 (cont): BMA Posterior Estimates Midwest Rural Property Crime

	Burglary		Larceny		Motor	
Percent of Population Age 15 to 24	***-0.09230***	***(0.0312)***	-0.05819	(0.4571)	-0.01465	(0.1226)
Percent of Population Age 75 plus	-0.09072	(0.2099)	-0.04882	(0.7164)	-0.02388	(0.1628)
Percent of the Population Caucasian	0.00085	(0.9850)	0.03136	(0.5635)	-0.00472	(0.6557)
Percent of the Population African American	-0.01573	(0.6643)	-0.00547	(0.9491)	***-0.02658***	***(0.0116)***
Percent of the Population Hispanic	-0.00070	(0.9857)	-0.01909	(0.8133)	-0.00223	(0.8180)
Ethnic Diversity Index	-0.14986	(0.9130)	-0.02800	(0.9755)	-0.00638	(0.9645)
Percent of those over 25 with a High School Education	0.00119	(0.9666)	0.00346	(0.9453)	-0.00809	(0.1908)
Percent of those over 25 with a Bachelor's Degree	-0.02099	(0.4974)	-0.00028	(0.9959)	-0.00310	(0.6953)
Percent of the Population Foreign Born 2000	-0.00072	(0.9929)	-0.03175	(0.8404)	-0.00017	(0.9926)
Percent of the Population Non-English Speakers at Home 2000	-0.04242	(0.1131)	-0.00241	(0.9648)	-0.00824	(0.2280)
Percent in Same Household 1995-2000	***-0.05525***	***(0.0275)***	-0.03826	(0.4102)	***-0.01758***	***(0.0029)***
Percent Change in Medicate Payments 2000-2005	-0.00002	(0.9995)	0.01281	(0.7682)	0.00000	(0.9999)
Percent of Houses Owner Occupied 2000	0.00002	(0.9996)	-0.00002	(0.9998)	-0.00119	(0.8944)
Percent of Households Living in Multiple Unit Housing 2000	***-0.09696***	***(0.0005)***	***-0.17978***	***(0.0007)***	***-0.01899***	***(0.0054)***
Per Capita Local Government General Revenues 2002	0.00000	(0.9985)	0.00026	(0.2867)	-0.00004	(0.1482)
Percent of Voters Voting Republican in 2004 Presidential Election	0.07309	(0.8438)	0.15676	(0.5481)	0.01047	(0.8983)
Percent of Voters Voting Democratic in 2004 Presidential Election	0.07564	(0.8286)	0.14504	(0.8376)	0.01228	(0.8750)
Gini Coefficient of Income Equality 1999	0.02926	(0.9960)	-0.61779	(0.9281)	-0.49351	(0.6207)
Percent Change in Gini Coefficient 1989-1999	***5.65255***	***(0.0000)***	4.28191	(0.1214)	0.00010	(0.9998)
Social Capital Index	***-0.38715***	***(0.0010)***	-0.30213	(0.1740)	-0.03999	(0.1400)
Adjancent to a Metro County	0.00000	(1.0000)	0.00000	(1.0000)	0.00000	(1.0000)
Remote Rural County	0.00000	(1.0000)	0.21796	(0.5729)	0.00000	(1.0000)
R^2	0.3419		0.2497		0.2659	
Number of Models	7,894		6,989		8,808	

t-test probability in parentheses

Appendix Table 3: Frequency of BMA Selection with P(Mj|y) Posterior Probability Greater than 1%.

	Murder	Rape	Robbery	Assault	Burglary	Larceny	Motor
Population Density	100.0%	13.3%	0.0%	90.9%	0.0%	100.0%	0.0%
Net Migration 2000-2006	0.0%	0.0%	100.0%	0.0%	33.3%	0.0%	88.9%
Population	0.0%	0.0%	0.0%	0.0%	0.0%	9.1%	0.0%
Per Capita Income	0.0%	0.0%	14.3%	0.0%	0.0%	9.1%	11.1%
Percent Change in Per Capita Income	28.6%	13.3%	0.0%	100.0%	0.0%	0.0%	0.0%
Earnings Per Job	100.0%	6.7%	0.0%	100.0%	5.6%	0.0%	0.0%
Percent Change in Earnings per Job	14.3%	46.7%	100.0%	0.0%	94.4%	0.0%	11.1%
Wage and Salaries per Job	0.0%	86.7%	0.0%	0.0%	0.0%	0.0%	0.0%
Percent Change in Wages and Salary per Job	0.0%	40.0%	42.9%	0.0%	22.2%	0.0%	0.0%
Number of Jobs	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Percent Change in Number of Jobs	0.0%	66.7%	0.0%	0.0%	0.0%	100.0%	0.0%
Unemployment Rate 2006	57.1%	100.0%	71.4%	0.0%	0.0%	100.0%	0.0%
Percent Change in the Unemployment Rate 2000-2006	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	100.0%
Per Capita Unemployment Insurance Income	100.0%	0.0%	0.0%	0.0%	100.0%	0.0%	33.3%
Percent Change in Per Capita Unemployment Insurance Income 2000-2007	42.9%	0.0%	0.0%	63.6%	0.0%	0.0%	0.0%
Poverty Rate 2004	0.0%	100.0%	100.0%	0.0%	27.8%	18.2%	0.0%
Percent Change in Poverty Rate 2000-2004	0.0%	0.0%	14.3%	0.0%	100.0%	0.0%	77.8%
Per Capita Income from Income Maintenance Programs	0.0%	100.0%	100.0%	9.1%	0.0%	100.0%	0.0%
Percent Change in Per Capita Income from Income Maintenance Programs	85.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Creative Class Index 2000	71.4%	0.0%	0.0%	0.0%	0.0%	36.4%	0.0%
Bohemian Class Index 2000	14.3%	33.3%	0.0%	0.0%	0.0%	9.1%	0.0%
Percent of Population Age 15 to 24	57.1%	0.0%	0.0%	100.0%	100.0%	0.0%	100.0%
Percent of Population Age 75 plus	100.0%	0.0%	100.0%	90.9%	100.0%	0.0%	100.0%
Percent of the Population Caucasian	100.0%	100.0%	85.7%	54.5%	11.1%	63.6%	33.3%
Percent of the Population African American	0.0%	100.0%	0.0%	36.4%	38.9%	0.0%	100.0%
Percent of the Population Hispanic	0.0%	33.3%	0.0%	36.4%	0.0%	0.0%	0.0%
Ethnic Diversity Index	0.0%	0.0%	0.0%	18.2%	0.0%	0.0%	11.1%
Percent of those over 25 with a High School Education	42.9%	100.0%	0.0%	9.1%	0.0%	0.0%	100.0%
Percent of those over 25 with a Bachelor's Degree	0.0%	0.0%	0.0%	9.1%	100.0%	0.0%	44.4%
Percent of the Population Foreign Born 2000	0.0%	0.0%	42.9%	27.3%	0.0%	0.0%	0.0%
Percent of the Population Non-English Speakers at Home 2000	14.3%	0.0%	0.0%	0.0%	94.4%	0.0%	88.9%
Percent in Same Household 1995-2000	28.6%	0.0%	0.0%	100.0%	100.0%	0.0%	100.0%
Percent Change in Medicate Payments 2000-2005	14.3%	100.0%	42.9%	0.0%	0.0%	54.5%	0.0%
Percent of Houses Owner Occupied 2000	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Percent of Households Living in Multiple Unit Housing 2000	85.7%	0.0%	0.0%	100.0%	100.0%	100.0%	100.0%
Per Capita Local Government General Revenues 2002	0.0%	0.0%	0.0%	100.0%	0.0%	90.9%	100.0%
Percent of Voters Voting Republican in 2004 Presidential Election	14.3%	53.3%	0.0%	63.6%	38.9%	72.7%	55.6%
Percent of Voters Voting Democratic in 2004 Presidential Election	14.3%	53.3%	57.1%	63.6%	38.9%	18.2%	22.2%
Gini Coefficient of Income Equality 1999	14.3%	100.0%	0.0%	0.0%	11.1%	0.0%	44.4%
Percent Change in Gini Coefficient 1989-1999	0.0%	100.0%	0.0%	0.0%	100.0%	100.0%	0.0%
Social Capital Index	100.0%	0.0%	100.0%	0.0%	100.0%	0.0%	100.0%
Adjacent to a Metro County	0.0%	100.0%	0.0%	100.0%	0.0%	0.0%	0.0%
Remote Rural County	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%